

PRODUCTIVITY, ECONOMIES, AND EFFICIENCY IN U.S. AGRICULTURE: A LOOK AT CONTRACTS

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The growing importance of production contracts, especially for some livestock species and in certain regions, suggests that contracts confer economic benefits on farmers. This trend has, however, stimulated concerns about the impacts of contracting on farm structure and concentration, and environmental degradation, which have led to efforts by various levels of government to regulate contract production.

For example, in the U.S. hog industry, between 1992 and 1998 the portion of feeder pig-to-finish hog operations using production contracts increased from 11% to 34%, while the share of output produced under contract increased from 22% to 63% (Key and McBride, McBride and Key). Recent growth in hog contracts have been particularly noteworthy in the upper Midwest, with 2002 contracted production accounting for 47% of the value of total farm production in Iowa and Minnesota, compared to only about 5% in 1996 and virtually none in 1991. Meanwhile, production contract levels in North Carolina, the other center of hog production, have been relatively stable.

Production contracts offer several potential advantages over independent production that could explain their increasing prevalence, such as lowering income risk for growers. Contracting may also raise farm productivity by improving the quality of managerial inputs, speeding the transfer of technical information to growers, and facilitating growers' access to credit, thereby permitting the adoption of newer, more efficient technologies. At the same time,

contractors gain by their access to grower resources and ability to exploit economies of size in livestock production. Future trends in agricultural production contracting will thus depend on the scope of these benefits, as well as the future viability of cash markets and the pace of vertical integration.

United States agricultural production patterns suggest that observed structural changes in U.S. agriculture such as the expansion of contracting are linked to scale and technical efficiencies, so that larger operations are increasingly more productive than small farms. Kumbhakar, Biswas, and Bailey (for dairy farms) and Sharma, Leung, and Zaleski (for hog farms) provide evidence that larger farms tend to be more technically efficient. Paul and Nehring and Paul et al. similarly link concentration in corn and livestock farming to scale and scope economies and efficiencies.

There is less direct evidence regarding the potential economies associated with the use of contracts. Some research, however, suggests that hog production contracts are associated with substantial productivity increases (Key and McBride). This implies that efforts to regulate contracting operations may have significant economic costs, even though they may also have positive environmental implications in terms of limiting environmental damage from waste.¹

In this article we consider the economic performance impacts of livestock production contracts and associated waste generation. To evaluate these impacts we estimate the effects of increased contracts and waste on productivity, efficiency and scale economy (SE) measures, for farms in different size (typology)² ranges, and with varying proportions of

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¹ In this article waste refers to manure nutrients produced by livestock. The farm survey data used in this study indicate that production of manure nutrients is higher on contract operations than independent operations.

² Farm typologies are distinguished by sales, operator occupation, assets, and total household income of the farm, as summarized in Hoppe, Perry, and Banker.

contracted production. We base our empirical analysis on a farm-level production dataset, recognizing a broad range of outputs and inputs, for 1991–2002.

We use an input distance function approach to represent farms' technological structure in terms of minimum input use required to produce given output levels, because farmers typically have more short-term control over their input than output decisions. The resulting theoretical framework characterizes input contributions per acre, which is consistent with analysis of yields in traditional agricultural studies but stems theoretically from the homogeneity properties of the distance function. This primal representation allows us to measure production structure indicators such as marginal input/output contributions and SEs, and has advantages over dual measures representing economic optimizing behavior, both because we do not have data on prices across observations, and because one might not wish to assume full price responsiveness, due to input fixities and time lags in farmers' observation of output prices.

We estimate our model by stochastic production frontier (SPF) methods, using data from an annual U.S. Department of Agriculture (USDA) survey of farms, where fattened cattle, hogs, and dairy are major components of agricultural output. The farm-level data are used to construct a pseudo-panel data set in terms of cohorts, to deal with the problem of linking annual cross-section data over time. We distinguish crop (corn, soybeans, cotton, "other") and livestock outputs, and land, labor, capital, fuel, chemicals (fertilizer, pesticides), materials (feed, seed, and "other"), and specific crop and animal inputs. The SPF methods used allow us to estimate both technical efficiency (TE) as a one-sided error term, and its determinants through the stochastic specification.

We find that smaller livestock farms are less scale and technically efficient than larger farms. Although increased contract use (and to some extent waste production) augment the input-saving associated with these efficiencies, the separate magnitude of these impacts is quite small. This may reflect the close link between contracting and farm size; commercial farms do the most contracting. These results suggest a competitive advantage of larger contracted operations over smaller independent operations, but that the primary impact arises from scale effects.

The Data

The U.S. farm-level data used to construct the panel data set are from the 1991–2002 Agricultural Resources Management Study (ARMS), Phase III survey. This is an annual survey covering U.S. farms in the forty-eight contiguous states, conducted by the National Agricultural Statistics Service, USDA, in cooperation with the Economic Research Service. Our data cover ten primary corn-producing states in the Heartland and selected livestock states and agricultural statistics districts: Illinois, Indiana, Iowa, Kansas (including New Mexico, Oklahoma, and the Texas panhandle to capture fattened cattle and hog production), Missouri, Ohio (including Kentucky, North Carolina and Virginia to capture hog production), Nebraska (including Colorado, North Dakota and South Dakota to capture fattened cattle production), Michigan (including New York and Pennsylvania to capture traditional dairy production), Minnesota, and Wisconsin.

These data include information on the value of marketing and production contracts by crop and livestock species (*CONT*), and on manure nitrogen production per cultivated acre, (waste, *WAST*).³ We also have data on the percentage of acres in biotech corn, soybeans, and cotton, GM_{CRN} , GM_{SOY} , GM_{COT} , and pesticide inputs, X_P . Additional outputs and inputs distinguished for our analysis include five specific outputs: Y_{CRN} = corn, Y_S = soybeans, Y_{COT} = cotton, Y_C = other crops, and Y_A = livestock; and nine inputs, X_{LD} = land, X_L = labor, X_K = capital, X_E = energy (fuel), X_F = fertilizer, X_{FD} = feed, X_{SD} = seed, X_C = other crop-specific materials, X_A = other animal-specific materials, and X_O = all other operating expenses. Time dummies, $t_{1992}-t_{2002}$, are also included as fixed effects.

Agricultural outputs are computed as the sum of the value of sales for each type of farm product, in dollars per farm. The variable inputs are annual per-farm expenditures on each input category. Capital machinery and land are measured as the annualized flows of capital services from assets and land. All these variables are deflated by the estimated increase or decrease in agricultural production prices in 1992–2002 compared to 1991.⁴

³ This is based on survey inventory data and the estimated production of manure and nitrogen by species, as calculated in Kellogg et al.

⁴ These deflators are computed using the indexes of prices received and paid (1990–92 = 100), Ag Statistics.

Table 1. Summary Statistics 2001–02

	Full Sample	RES	SM	LG	VLG
Percentage of weighted (population) farms	100	54.18	26.79	11.60	7.43
Percentage of weighted acres	100	18.97	22.69	29.05	29.29
Percentage of weighted output	100	8.53	10.18	22.00	59.29
Livestock (\$/farm)	75,024	10,914	23,259	119,950	659,751
Manure N (lb/acre)	7.77	2.61	4.14	7.09	12.35
Contracting (percentage of production)	35.24	5.02	9.37	19.21	49.97

Analysis of the economic performance of livestock farms and their determinants cannot, however, be conducted on ARMS data directly. The ARMS survey collects annual cross-section data, which are not directly amenable to the analysis of panel data, as needed for time series analysis. We circumvent this problem by using repeated cross-sections of data across farm typologies to construct a cohort approximation of panel data. Such a panel is created by grouping the individual observations into homogeneous cohorts, distinguished according to time-invariant characteristics, and using the cohort means rather than the individual farm-level observations for empirical estimation.

We assigned the farm-level data to cohorts based on farm type (retirement and residential, family, and corporate farms) and size (sales), as discussed in Paul et al. The resulting pseudo-panel data are the weighted mean values of the variables to be analyzed, by cohort, state, and year. We thus have a balanced panel of 1,560 annual observations (130 per year, for our ten-state sample). For presentation of our results, we group these cohorts into residential farms (RES), small family farms (SM), larger family farms (LG), and very large family and nonfamily farms (VLG), and distinguish low (LOW), medium (MED) and high (HIGH) contracting-intensive states.⁵ To assure a large number of observations per cohort for regional analysis we aggregated the annual data to two-year cells, summarizing the activities of 3,097 farms in 1991/92, 2,599 farms in 1993/94, 4,731 farms in 1995/96, 6,784 farms in 1997/98, 6,307 farms in 1999/2000, and 5,201 farms in 2001/2. Some summary statistics for 2001/2, presented in table 1, document the sharp rise across farm size in the value of livestock production, production contracts, and manure nutrient production per acre in these data.

The Model

Empirical analysis of economic performance requires representing the underlying multidimensional (input and output) production technology. A general form for such a technology may be characterized by an input set, $L(\mathbf{Y}, \mathbf{R})$, summarizing the production frontier in terms of the set of all input vectors \mathbf{X} that can produce the output vector \mathbf{Y} , given the vector of shift and environmental variables \mathbf{R} (the *CONT*, *WAST*, and *GM* indicators and time dummies). From this production set we can specify an input distance function (denoted by superscript I) that identifies the minimum possible input levels for producing a given output vector as follows:

$$(1) \quad D^I(\mathbf{X}, \mathbf{Y}, \mathbf{R}) = \max\{\rho : (\mathbf{X}/\rho) \in L(\mathbf{Y}, \mathbf{R})\}.$$

$D^I(\mathbf{X}, \mathbf{Y}, \mathbf{R})$ is, therefore, essentially a multi-input input-requirement function, representing the production technology while allowing deviations from the frontier.

We estimate this function using SPF techniques, assuming TE is imputed as a radial contraction of inputs to the frontier (constant input composition). The econometric model includes two error terms, a random error term, v , assumed to be normally distributed, and a one-sided error term, u , assumed to be distributed as a half normal, to represent the distance from the frontier.

Estimating $D^I(\mathbf{X}, \mathbf{Y}, \mathbf{R})$ requires imposing linear homogeneity in input levels (Färe and Primont), which is accomplished through normalization (Lovell et al.); $D^I(\mathbf{X}, \mathbf{Y}, \mathbf{R})/X_1 = D^I(\mathbf{X}/X_1, \mathbf{Y}, \mathbf{R}) = D^I(\mathbf{X}^*, \mathbf{Y}, \mathbf{R})$.⁶ Approximating this function by a translog functional form to limit *a priori* restrictions on the relationships among its arguments results in

⁵ LOW states are Illinois, Indiana, Missouri, Michigan, and Wisconsin. MED states are South Dakota (including Kansas) and Nebraska. HIGH states are Iowa, Ohio, and Minnesota.

⁶ By definition, linear homogeneity implies that $D^I(\omega\mathbf{X}, \mathbf{Y}, \mathbf{R}) = \omega D^I(\mathbf{X}, \mathbf{Y}, \mathbf{R})$ for any $\omega > 0$; so if ω is set arbitrarily at $1/X_1$, $D^I(\mathbf{X}, \mathbf{Y}, \mathbf{R})/X_1 = D^I(\mathbf{X}/X_1, \mathbf{Y}, \mathbf{R})$.

$$\begin{aligned}
(2a) \quad \ln D_{it}^I / X_{1,it} &= \alpha_0 + \sum_m \alpha_m \ln X_{mit}^* \\
&+ 0.5 \sum_m \sum_n \alpha_{mn} \ln X_{mit}^* \ln X_{nit}^* \\
&+ \sum_k \beta_k \ln Y_{kit} \\
&+ 0.5 \sum_k \sum_l \beta_{kl} \ln Y_{kit} \ln Y_{lit} \\
&+ \sum_q \phi_q R_{qit} \\
&+ 0.5 \sum_q \sum_r \phi_{qr} R_{qit} R_{rit} \\
&+ \sum_k \sum_m \gamma_{km} \ln Y_{kit} \ln X_{mit}^* \\
&+ \sum_q \sum_m \gamma_{qm} \ln R_{qit} \ln X_{mit}^* \\
&+ \sum_k \sum_q \gamma_{kq} \ln Y_{kit} \ln R_{qit} + v_{it} \\
&= TL(X^*, Y, R) + v_{it} \text{ or}
\end{aligned}$$

$$\begin{aligned}
(2b) \quad -\ln X_{1,it} &= TL(X^*, Y, R) + v_{it} - \ln D_{it}^I \\
&= TL(X^*, Y, R) + v_{it} - u_{it}
\end{aligned}$$

where i denotes farm, t the time period, k and l the outputs, m and n the inputs, and q and r the \mathbf{R} variables. We specify X_1 as land, so the function is specified on a per-acre basis, consistent with much of the literature on farm production in terms of yields.

In addition, the distance from the frontier, $-\ln D_{it}^I$, is explicitly characterized as the technical inefficiency error $-u_{it}$. As in Battese and Coelli,⁷ we use maximum likelihood (ML) methods to estimate (2b) as an error components model, assuming $-u_{it}$ is a nonnegative random variable independently distributed as a truncation at zero of the $N(m_{it}, \sigma_u^2)$ distribution, where $m_{it} = \mathbf{R}_{it}\delta$, \mathbf{R}_{it} is a vector of farm efficiency determinants (assumed here to be the factors in the \mathbf{R} vector), and δ is a vector of estimable parameters. The random error component v_{it} is assumed to be independently and identically distributed, $N(0, \sigma_v^2)$.

The productivity impacts (marginal productive contributions, MPC) of outputs or inputs can be estimated from this model by the first-order elasticities $MPC_k = -\epsilon_{DI,Yk} = -\partial \ln D^I(X, Y, \mathbf{R}) / \partial \ln Y_k = \epsilon_{X1,Yk}$ and $MPC_m = -\epsilon_{DI,X^*k} = -\partial \ln D^I(X, Y, \mathbf{R}) / \partial \ln X_m^* = \epsilon_{X1,X^*m}$. MPC_k indicates the increase in overall input use when output expands (and so should be positive, like a marginal cost or output elasticity measure), and MPC_m indicates the shadow value (Färe and Primont) of the m th input relative to X_1 (and so should be negative, like the

slope of an isoquant). Similarly, the marginal productive contributions of structural factors ($CONT$, $WAST$, and the time shifters) can be measured through the elasticities $MPC_{R_q} = -\epsilon_{DI,R_q} = -\partial \ln D^I(X, Y, \mathbf{R}) / \partial R_q = \epsilon_{X1,R_q}$ (if $\epsilon_{X1,R_q} < 0$, increased R_q implies that less input is required to produce a given output, which implies enhanced productivity, and vice versa).⁸

Scale economies are calculated as the combined contribution of the K outputs Y_k , or the scale elasticity $SE = -\epsilon_{DI,Y} = -\sum_k \partial \ln D^I(X, Y, \mathbf{R}) / \partial \ln Y_k = \epsilon_{X1,Y}$. That is, the sum of the input elasticities, $\sum_k \partial \ln X_1 / \partial \ln Y_k$, indicates the overall input–output relationship and thus returns to scale. The extent of scale economies is thus implied by the shortfall of scale economies from 1; if scale economies < 1 inputs do not increase proportionately with output levels, implying increasing returns to scale.

The second-order effects of the \mathbf{R} factors on output and input contributions and overall SEs can, in turn, be measured as

$$\begin{aligned}
\epsilon_{MPCk,R_q} &= -\partial \ln \epsilon_{DI,Yk} / \partial R_q \\
&= -\partial^2 \ln D^I(X, Y, \mathbf{R}) / \partial \ln Y_k \partial R_q, \\
\epsilon_{MPCm,R_q} &= \partial \ln \epsilon_{DI,X^*m} / \partial R_q \\
&= -\partial^2 \ln D^I(X, Y, \mathbf{R}) / \partial \ln X_m^* \partial R_q
\end{aligned}$$

and

$$\epsilon_{SE,R_q} = \partial \ln SE / \partial R_q.$$

These measures, therefore, indicate whether, for example, more contracting increases or reduces the input use associated with production of Y_k .

Finally, TE “scores” are estimated as $TE = \exp(-u_{it})$. The impact of changes in R_q on TE can also be measured by the corresponding δ coefficient in the inefficiency specification for $-u_{it}$.

The Empirical Results

Although most of the parameter estimates (available on request from the authors) are not

⁷ We used Tim Coelli's FRONTIER package for the SPF estimation, and computed the measures using PC-TSP.

⁸ Note that a standard “productivity” or “technical change” measure, usually defined as the elasticity with respect to time, or the time trend of the input–output relationship, is not targeted here. Elasticities with respect to the time dummies provide indications of production frontier shifts for each time period, but for short time series other external factors such as weather often confound estimation of a real technical change trend.

Table 2. Second-Order Impacts of *CONT* and *WAST*

SE Elasticities	Estimate	<i>t</i> -Statistic	MPC Elasticities	Estimate	<i>t</i> -Statistic
ε _{SE,CONT}	−0.0008	−4.58	ε _{MPCYC,CONT}	0.0018	3.50
ε _{SE,WAST}	0.0001	2.72	ε _{MPCYC,WAST}	0.0002	3.68
			ε _{MPCYA,CONT}	−0.0026	−6.59
			ε _{MPCYA,WAST}	−0.0001	−3.60

Table 3. Estimated Scale Economies, Technical Efficiency, and Marginal Productivity Contributions for *CONT* and *WAST*

Performance Measures	Full Sample	<i>t</i> -Statistic	LOW	<i>t</i> -Statistic	MED	<i>t</i> -Statistic	HIGH	<i>t</i> -Statistic
SE	0.656	73.65	0.658	70.14	0.642	66.18	0.663	74.90
TE	0.858		0.857		0.857		0.860	
MPC _{CONT}	−0.013	−11.45	−0.014	−11.99	−0.011	−8.60	−0.014	−11.89
MPC _{WAST}	0.0002	1.47	0.0002	1.23	0.0004	2.13	0.0002	1.29
	RES	<i>t</i> -Statistic	SM	<i>t</i> -Statistic	LG	<i>t</i> -Statistic	VLG	<i>t</i> -Statistic
SE	0.471	45.10	0.523	54.85	0.760	73.39	0.872	67.71
TE	0.779		0.838		0.894		0.915	
MPC _{CONT}	−0.011	−12.19	−0.012	−11.99	−0.014	−10.65	−0.016	−11.51
MPC _{WAST}	0.0001	1.11	0.0002	1.24	0.0003	1.71	0.0003	1.45

very explanatory due to the flexible functional form (so the elasticity measures are combinations of various parameters and data), some estimates are directly interpretable. In particular, the productive impacts of both *CONT* and *WAST* ($\gamma_{YA,CONT} = 0.002$, $\gamma_{YC,CONT} = -0.003$, $\gamma_{YA,WAST} = 0.0002$, and $\gamma_{YC,WAST} = -0.0001$) are statistically significant, although reversed in sign. That is, increased contracting and waste appear to increase the productive contribution of (decrease the inputs required for) livestock, but the reverse is true for “other” crops. This is consistent with the second-order productivity elasticities representing the effects of *CONT* and *WAST* on Y_A and Y_C in table 2. We also find that both *CONT* and *WAST* have a “productive” TE contribution through their δ coefficients ($\delta_{CONT} = 0.025$ and $\delta_{WAST} = 0.001$), although only for *CONT* is this contribution statistically significant at the 5% level.⁹

Table 3 reports the levels of our overall performance indicators (SE and TE), and the productive contributions (MPCs) of contracts and waste, for the whole sample, for different size farms, and for LOW, MED, and HIGH *CONT*-intensive states. The elasticity measures are

evaluated at the data averages for the particular sample under consideration, to allow estimation of standard errors through the delta method. The TE measures are averages of the estimated efficiency scores across all the observations in the sample.

The measures show strong SEs, which are greatest for smaller farms, indicating scale inefficiency for these farms (lower unit costs associated with growth, due to increasing returns to scale). By contrast, SEs do not seem closely related to the intensity of contracting. This is consistent with the second-order SE elasticities presented in table 2, that suggest that higher contracting and lower waste are both statistically significantly associated with greater SEs, but that the magnitude of the effect is small.

Technical efficiency also increases with farm size, with RES farms on average only reaching about 80% of full “best practice” efficiency, whereas VLG farms exhibit more than 90% efficiency. The variation in TE across different *CONT*-intensive states is again minimal, consistent with the significant but small estimates of inefficiency effects for *CONT* from the δ parameters mentioned above.

It thus appears that although contracting has a statistically significant impact on productivity, SEs, and TE, the economic significance (magnitude of impact) is smaller than that associated simply with the size of operations.

⁹ Although at an initial glance these results appear potentially inconsistent, since both high *CONT* and *WAST* levels might be expected to arise from livestock-intensive operations, high contracting likely reflects a greater proportion of large hog operations, and high *WAST* a greater proportion of large dairy-intensive operations.

Table 4. Estimated MPCs for Outputs, Inputs, and Time Shifts, Full Sample

MPC_{YS}	0.024	<i>5.15</i>	MPC_{XF}	0.021	<i>1.61</i>	MPC_{1993}	-0.204	-6.89
MPC_{YCOT}	0.003	<i>0.59</i>	MPC_{XL}	-0.381	-26.99	MPC_{1995}	-0.216	-7.56
MPC_{YO}	0.048	<i>11.93</i>	MPC_{XE}	-0.079	-5.27	MPC_{1997}	-0.301	-8.67
MPC_{YA}	0.489	<i>69.98</i>	MPC_{XSD}	-0.145	-9.90	MPC_{1999}	-0.330	-9.43
			MPC_{XFD}	-0.193	-22.05	MPC_{2001}	-0.229	-6.20
			MPC_{XA}	-0.068	-14.52			
			MPC_{XC}	0.011	<i>1.94</i>			
			MPC_{XO}	-0.050	-4.11			
			MPC_{XK}	-0.036	-2.39			
			MPC_{Xp}	-0.098	-7.15			

Note: *t*-statistics are in italics.

Table 4 presents the average *MPCs* across all observations for each output and input, as well as the time shifts (from the 1991–92 base), to further evaluate the estimated production patterns. The *MPCs* for the outputs represent the proportional “marginal cost” or input-use share of the output. By far the largest input share is devoted to animal or livestock outputs (Y_A)—nearly 50% on average (and increasing from 40% to almost 65% as one moves from smaller to larger farm sizes).

The *MPCs* for the inputs indicate the contribution of that input to overall input use (substitutability). The largest (in absolute value) *MPC* is for labor, followed by feed and seed. The positive estimated shadow values for fertilizer and crop-specific inputs may be due to the heavier reliance on livestock production of the farms in our sample. These estimates are, however, small with large standard errors; the difference of MPC_F from zero is insignificant and of MPC_C only marginally significant at the 5% level.¹⁰ The time dummies also indicate more productivity in terms of input per unit of output over time, except for 2001–2 (the ϕ_{2001} estimate is smaller than ϕ_{1997} , indicating an inward shift of the production frontier, due perhaps to some external factor such as weather).

Concluding Remarks

We have used an input distance function approach to evaluate scale and TE, and productive effects of contracting, for small as compared to large farming operations. We find that smaller operations and those with lower contracting levels are less efficient overall than larger-scale and contract-intensive entities, although the independent impact of contracts

is small. This suggests competitive pressures on smaller farms from the greater productivity (in terms of input use per unit of output) of larger farms—especially those that more heavily rely on contracts. It also suggests that more stringent requirements for larger operations or subsidization of smaller farms to meet regulatory requirements could have detrimental efficiency impacts.

In addition, since higher *CONT* and *WAST* levels are associated with greater productivity, scale economies, and TE, policies that raise costs on contracting to control concentration, and on waste disposal to limit environmental damage, may reduce overall cost efficiency. Our results also suggest, however, that these impacts are likely to be small unless the policies also provide incentives to limit the scale of production. Thus, one might expect the costs of such restrictions to be counterbalanced by the environmental and market benefits.

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¹⁰ These effects are the same across observations because they are simply based on the parameter estimates.

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